

Mapping Severe Fire Potential across the Contiguous United States

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Introduction

The Fire Severity Mapping System (FIRESEV) project is an effort to provide critical information and tools to fire managers that enhance their ability to assess potential ecological effects of wildland fire. A major component of FIRESEV is the development of a Severe Fire Potential Map (SFPM), a geographic dataset covering the contiguous United States (CONUS) that quantifies the potential for wildland fires to burn with higher severity should they occur (Dillon et al 2011a). We developed this map using empirical observations and statistical models to relate biophysical conditions at the time and location of a fire to the resulting severity. For our purposes, burn severity refers to the degree to which aboveground biomass has been altered as expressed in the change between pre- and post-fire satellite imagery (Lentile et al 2006). Our aim in creating the SFPM is to explore the relationships between site characteristics and burn severity (Dillon et al 2011b) and to provide land managers with a tool that can forecast the potential severity of future fires.

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Methodology

Building on the work of Holden et al 2009, we developed a set of statistical models, each relating a suite of independent geospatial variables to 30 years of burn severity data developed by the Monitoring Trends in Burn Severity (MTBS) project. MTBS is an ongoing project to map the severity of all large fires that have occurred since 1984 (Eidenshink et al 2007). We partitioned continuous measures of burn severity into a binary dataset of ‘higher severity’ vs. ‘lower severity’. We produced models to determine the relationship between the two severity classes and site characteristics such as pre-fire vegetation, temporally-specific 1000-hour fuel moistures and a suite of topographic variables. We developed these models separately for forest and woodland vs. non-forest settings in each of 25 distinct ecological regions. The resultant statistical models are used to estimate, based on current measures of our predictor variables, the probability that fire at a particular point on the landscape will result in higher burn severity, should that location burn. These results were used to create a digital map depicting severe fire potential for every 30-meter pixel across CONUS.

Study Area(s)

Our study area consisted of the entirety of CONUS but we completed the project in two phases, the west in 2012 and the east in 2016. Because fire behaves differently under disparate biophysical and climatic conditions it was necessary to divide our study area up into smaller subsets based on modified US EPA ecoregions (Omernik 1987) with some consolidation (Fig. 1). In addition, burn severity measurement and interpretation are different in forest and woodland vs. non-forest settings. Therefore, we further divided each mapping region into these two broad vegetation cover types. We used the mapping regions and cover types to stratify statistical modeling. This resulted in 50 predictive models (25 regions x 2 cover types).

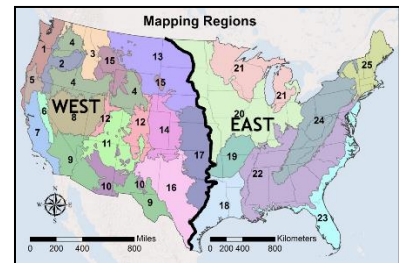


Figure 1: Mapping regions

Data acquisition

We obtained burn severity data for over 12,000 fires that occurred between 1984 and 2013 from MTBS (<http://www.mtbs.gov/index.html>). We divided the continuous measures of burn severity from MTBS into ‘severe’ vs. ‘not severe’ categories. Due to differences in the quantity and distribution of burn severity data, modeling methodologies differed slightly between the east and the west. One of these differences is the definition of a ‘severe’ fire. For the west, where high-severity fire is more commonplace, we divided the burned pixels into ‘high’ vs. ‘low to moderate’ severity categories. In the east, we divided burned pixels into ‘moderate to high’ vs. ‘low’ severity. Our methodologies for creating categorical definitions of low, moderate and high severity are comparable, but not identical, to those used by MTBS.

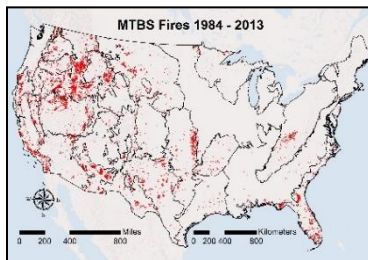


Figure 2: MTBS fires

For our site characteristic data, we acquired 30-meter Digital Elevation Models (DEMs) from the National Elevation Dataset (NED; <http://ned.usgs.gov/>) and used them to create a suite of

topographic indices. We also used the DEMs to model solar radiation, which reflects the influence of topography on vegetation. To represent pre-fire vegetation conditions in the west, we used the Normalized Difference Vegetation Index (NDVI), which we derived from pre-fire Landsat imagery acquired from MTBS. In the east, we obtained moderate-resolution imaging spectroradiometer (MODIS) NDVI data from the United States Geological Service (USGS; <https://lpdaac.usgs.gov/>). As a measure of seasonal drought, we used 1000-hour fuel moistures at the time of each fire in our dataset. Fuel moisture data were derived using 4km resolution downscaled North American Regional Reanalysis (NARR) data (Abatzoglou 2013). A total of 17 variables were developed as predictive inputs.

Modeling

Once we had acquired and processed the input data, we generated a spatially-balanced, random sample representing 1% of all burned pixels. We used the ~ two million sample point locations to extract values for all of our predictor variables.

We used the Random Forest machine-learning algorithm (Breiman 2001) to develop our statistical models. Random Forest is an extension of classification and regression tree modeling techniques. It divides inputs into training and testing datasets and uses the training data to create models and the testing data to validate the accuracy of its models. Random Forest also has the ability to rank how important each input variable is in terms of its predictive power. We used Random Forest modeling with 1500 classification trees and selected the optimal model with the lowest classification error. This resulted in 50 separate Random Forest models, one each for forest and woodland and non-forest cover types in each of our 25 mapping regions.

Results

Our Random Forest modeling results showed a strong relationship between site characteristics and the resultant burn severity. In forest and woodland cover types cross-validated classification

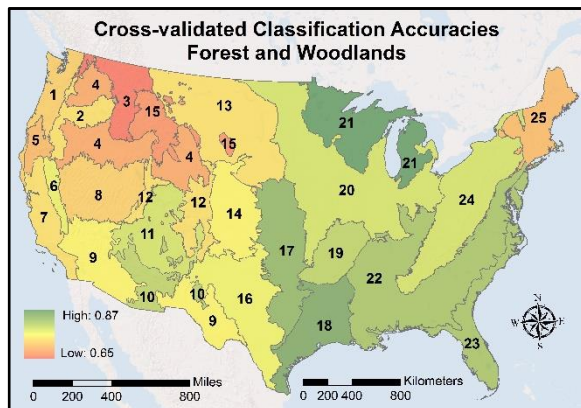


Figure 3: Classification accuracies – Forest & Woodlands

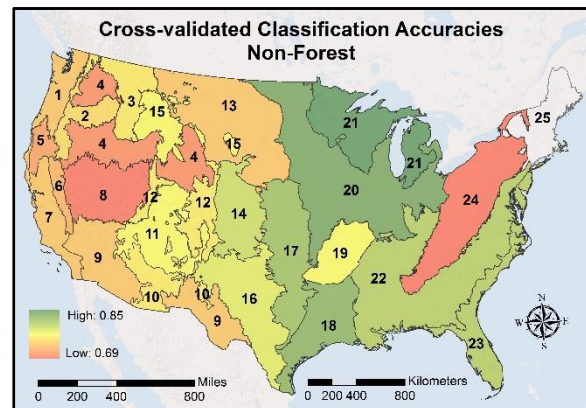


Figure 4: Classification accuracies - Non-Forest

accuracies ranged from 65 to 87% with a median of 73% (Fig. 3). In the non-forested areas, classification accuracies ranged from 69 to 85% with a median of 76% (Fig. 4). The number of

predictor variables selected in the optimal Random Forest models ranged from four to ten in the forest and woodlands models and four to nine in the non-forest models with medians of six and seven respectively. In terms of variable importance rankings, elevation, 1000-hr fuel moisture and NDVI were generally in the top four predictor variables, often with some combination of solar radiation, slope and broad-scale topographic position.

Mapping

Using the Random Forest models created in the modeling process, we predicted potential burn severity using contemporary landscapes with spatially-comprehensive and temporally-

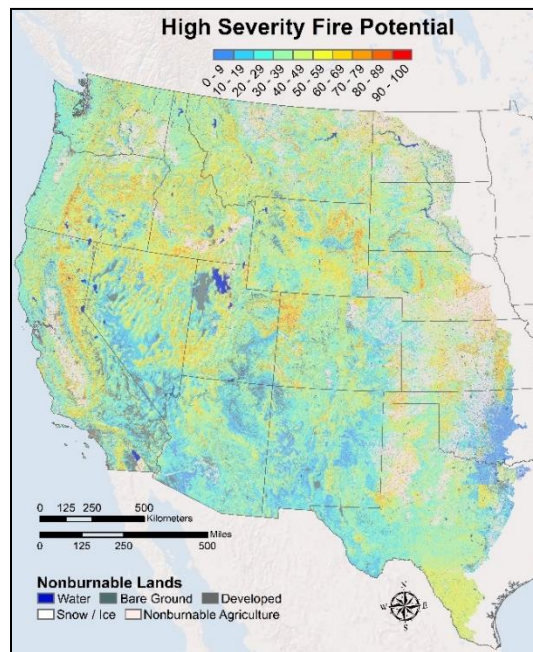


Figure 5: Western burn severity potential

Discussion

When coupled with information regarding current landscape conditions, the Severe Fire Potential Map can assist managers in identifying areas where fire may help restore fire-adapted ecosystems and where it might have less favorable impacts. Its potential uses include:

- Planning for future wildfires - pre-existing product can inform managers as to whether an ignition may lead to desirable or undesirable ecological impacts.

representative predictor variables. Topographic variables are static but vegetation and 1000-hour fuel moistures are not. We used recent NDVI vegetation data and constant 1000-hour fuel moisture values at a variety of common fire weather thresholds (80th, 90th and 97th percentiles). Constant fuel moisture values are necessary because it is not possible to know them in advance. Each of the 1500 classification trees in the Random Forest models classify every 30-meter pixel on the landscape into either the severe or not severe categories resulting in 1500 predictions of binary severity. The product of this analysis is a map showing the percentage of classification trees that predicted severe fire. Figures 5 and 6 show the results of these predictions at the 90th percentile 1000-hour fuel moisture level for the west and the east respectively. In the west, we are forecasting the potential for high severity fire and in the east the potential for moderate to high severity fire.

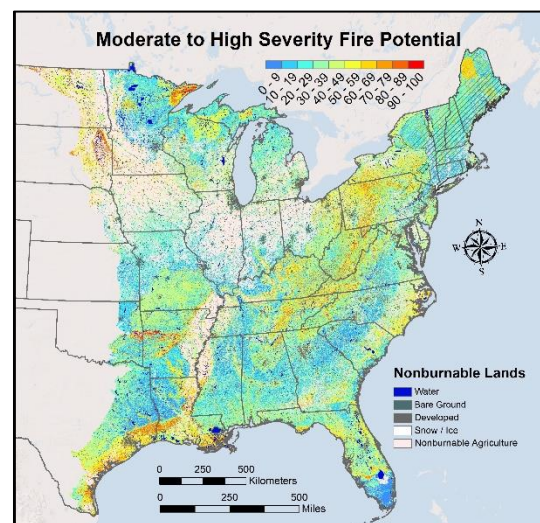


Figure 6: Eastern burn severity potential

- Planning prescribed burns – informs potential ecological consequences of prescribed fire.
- Fuel treatment planning – helps managers focus on areas where fire may burn with an undesirable severity.
- Immediate post-fire rehabilitation – identifying those areas most likely to need mitigation treatments (e.g. soil stabilization) before traditional post-fire burn severity products (e.g. BAER and RAVG) are available.

The completed SFPM is currently available online at <http://www.frames.gov/firesev> for the western US and at <http://www.frames.gov/firesev/east> for the eastern US. This map product will be incorporated into existing decision support frameworks such as the Wildland Fire Decision Support System (WFDSS) in the near future. A General Technical Report (GTR) describing the methods, map products and validation metrics is also forthcoming. The development of the Severe Fire Potential Map has provided an opportunity to enhance our understanding of the environmental influences on burn severity and has provided a new resource to support fire management decisions.

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